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# System relevant Applications for Battery Storage Systems

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**Abstract:** By the end of 2015, more than 36,000 battery storage systems in combination with PV systems had been installed in Austria and Germany. As yet, these battery storage systems are mainly used to increase the on-site consumption of local PV generation. However, charging the battery without considering the current generation of the PV system and the current state of the grid, means that this application is of little benefit for the grid, e. g. regarding control and stability, reliability, power quality or security. Alongside the use of battery storage systems to limit a PV system's maximum grid feed-in, several other grid and/or system-relevant applications for battery storage systems are possible. One strategy is to use autonomous systems to even out a buildings' load peaks, mainly caused by heat pumps or other electric heating or cooling systems. Forecast-based operation strategies are required. The research project Spin.OFF uses a self-learning artificial neural network (ANN) to predict the energy demand of buildings. In addition to local autonomous strategies, some system- and/or grid-relevant applications require coordination by third parties. The second strategy, presented in research project MBS+, provides a decentralized micro-grid concept for the optimization of Distributed Energy Resources (DER) in the form of a Battery-Storage-Network (BSN).

**Keywords**: battery storage systems, battery storage network, grid-relevant applications, artificial neural network, social implications

## Introduction

By the end of 2015, more than 36,000 battery storage systems in combination with photovoltaic (PV) systems had been installed in Austria and Germany (Kairies et al, 2016). Investment subsidies and the desire of private households for energy self-sufficiency are the main drivers for this trend, which is most likely to continue to increase in the future. These systems are mainly used to maximise the on-site consumption of the local PV generation. However, charging the battery without considering the current generation of the PV system and the current state of the grid, means that this application is of little benefit for the grid or the energy system (Weniger et al, 2016). Taking into account the public subsidies for such battery storage systems, it seems to be economically feasible to also use these battery systems within a defined scope for system- or grid-relevant applications, because the inter-connection of an rapidly increasing number of Distributed Energy Ressources (DER) to the grid causes more and more problems of control and stability and also raises concerns about reliability, power quality, and security. One potential grid-relevant application is the use of these battery storage systems to even-out the PV system's grid feed-in. This application is mandatory in the German support programme for battery storage systems, where the maximum PV feed-in is limited to 50 % of the nominal PV power (since 2016) to ensure that PV peaks are always eliminated (Weniger et al, 2016).

**System-relevant applications for decentralized autonomous energy storage systems**

A grid-relevant application for battery storage systems is currently being investigated in a case study of an office building under construction in Vienna. The study implements an Aqueous Hybrid Ion (AHI™) battery storage system and answers questions concerning technical planning and dimensioning issues, ecological evaluation concerns, as well as its instrumental utilization to minimise power grid peak load or to maximise in-house consumption by means of an energy management system based on a self-learning artificial neural network approach (Maul et al, 2017). This section of the paper is concerned with first results of implementing and priming the energy management system with historical data from a comparable neighbouring office building.

In general, the energy consumption of office buildings can be divided into two parts. Tenant consumption, which is not a concern of this study, and the costs of operating the building, which are mainly caused by heat pumps or other electric heating or cooling systems, lighting, etc., but are also reduced by photovoltaic (PV) installations in the overall infrastructure of an office building. This mixture creates the need for energy management systems for the intelligent combination of resources, without changing the aim of evening-out load peaks and allowing for self-optimization. This case study implements a cradle-to-cradle certified battery implementation and 33 $kW_{peak}$ PV system, reflects the scenario described above, and tries to answer all the issues arising in implementation. It also opens the possibility of retrieving data which can be used for further research. After installation, a tenant survey will be conducted to study the social impact and acceptance of this type of system. Lastly, an ecological analysis including a lifecycle assessment will be carried out to highlight the advantages of AHI™ battery storage systems and compare the result with other battery systems, such as Li-ion, Vanadium, Zinc-Iron and Redox Flow in terms of ecological footprint.

The energy management system was based on the use of a self-learning artificial neural network (ANN), not possible to realize with traditional grid-connected converters and their limitations in their applicability to dynamic systems, lack of processing power and missing interfaces. An ANN is a computational model made by a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs. It was developed as a self-learning feed-forward artificial neural network (FF-ANN) to predict power consumption (D'Andrea et al, 2012). An analysis of the electrical and architectural concept of the battery system was conducted within the technical and regulatory limitations. The performance of electrical security devices during isolated operation is being investigated to confirm that these devices respond accurately, since currently this is still uncertain. The energy management system implemented was primed with data from a comparable neighbouring building, and battery performance is currently being analysed to acquire new data regarding the energy flow, power ramps, power availability and power quality to gain insights into the physically achievable flexibilities offered by the new AHI™ battery storage system to create a model predictive control (MPC) system, as a second part, to manage the battery storage. The FF-ANN uses solar radiation, net energy consumption, building temperature data along with a day categorization system as inputs, the purpose of which is to predict short-term net building power consumption, hence the energy demand of the office building, and the MPC, based on the consumption forecast and PV production forecast, will create a charging/discharging schedule for the battery storage system.

Once installed in the office building, the system will be periodically retrained (the optimum frequency is yet to be determined) to include changes in the energy use behaviour of the building due to occupancy changes and various changes in the building structure, for example, more energy-efficient windows, or retrofitting more solar panels for increased local energy production.

The ANN model developed, presented in (Xypolytou et al, 2017), different input combinations were examined during the design of the FF-ANN. The parameters that affect the performance of the ANN are types of input and their pre-processing, the number of hidden layers used, the size of the hidden layers, the transfer function that creates non-linearity between the layers, and the time window that determines the samples used for the training. In addition, it is very important for the retraining period to be chosen in such a way as to allow adaptability to new conditions without affecting the performance of the FF-ANN.

The selection process of the inputs was based on various simulations and a comparison between architectures (see Figure 1). Mean Square Error (MSE) between target data and simulated data of the comparable office building was used as a benchmark (Tofallis, 2015).

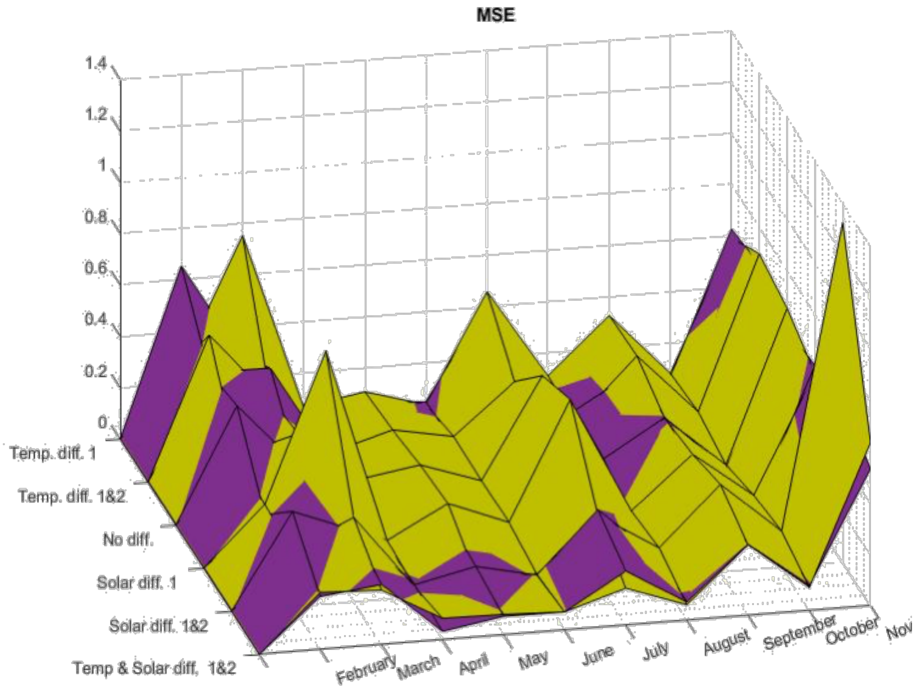


Figure 1. MSE comparison of 3 hidden layers (gold), size 7 neurons with 2 hidden layers and better performing (lower MSE) size 5 neurons (purple)

The current optimum set of inputs and pre-processing can be seen in Table 1.

Table 1. Input types and pre-processing

| Input | Pre-processing / Type of input |
|---|---|
| Past energy consumption | Moving average of 4 hours |
| Solar radiation | Moving average of 1 hour |

| | |
|---|---|
| 1st derivative of solar radiation | Moving average of 1 hour |
| 2nd derivative of solar radiation | Moving average of 1 hour |
| Temperature | Moving average of 2 hours |
| 1st derivative temperature | Moving average of 2 hours |
| 2nd derivative temperature | Moving average of 2 hours |
| Date | Specific day of week, month, and holiday |
| Time | Hour of day |

This FF-ANN consists of two hidden size 5 layers. The input layer has the 9 inputs shown in Table 1, while the output layer has size 1, which is the moving average of the next 4 hours. Each neural network layer has an integrated weight matrix (W) and bias vector (b). The transfer function of the hidden layers is the hyperbolic tangent sigmoid transfer function (tansig). The output layer is driven in a Log-sigmoid transfer function (logsig). The training time window used was 23 days. The Matlab® graphical representation of the current form of FF-ANN is shown in Figure 2:

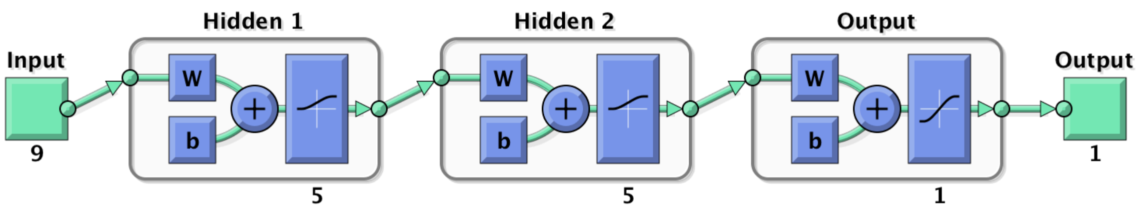


Figure 2. The current FF-ANN architecture in Matlab®

The power consumption projected by the FF-ANN and the actual consumption available in the historical test set is shown in Figure 3 below:

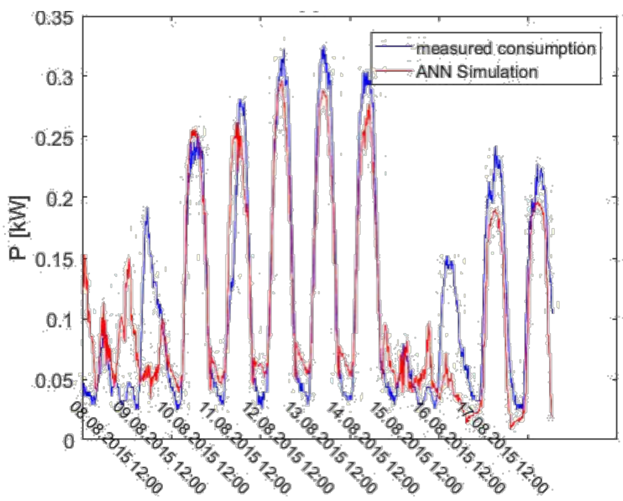


Figure 3. FF-ANN results on an exemplary 10-days test set

The system reflects choices made to create an FF-ANN the purpose of which is to predict the consumption of a building. It has the ability to be re-trained periodically. To achieve this, a local data storage will be integrated to save historical data. These data are a valuable source for the conduct of future studies which can further optimize local controllers.

***Technical implementation***

The technical approach involves connecting single battery storages (located in different households) to form a BSN. While these storages are connected to the power line, an additional communication network is required to enable these distributed storages to communicate and exchange information with each other.

To date, no or only limited support is available for collaboration among participants of a balancing group to utilize distributed storage devices for balancing generation schedule deviations. In particular, owners of PV systems and (private) battery storages are not able, e.g., to autonomously and jointly decide how to fulfil the requests of a balancing group officer (BGO) by using their aggregated battery storage potential.

Several approaches are considered feasible for fulfilling the given requirements of a decentralized BSN. Among them, peer-to-peer (P2P) technology (Oram, 2001; Fattah, 2002) represents quite an obvious choice. It is not only the notion of a computing architecture that does not rely on a central (server) component that makes P2P systems feasible for the envisaged BSN. In fact, there is an analogy between early P2P computing systems and the current discussion on the use of private and distributed PV systems and battery storages in a P2P manner. According to (Shirky, 2001), P2P applications take advantage of previously unused resources – storage, computing cycles etc. –, which allows them to make new, powerful use of a large number of devices that have been connected to the Internet. It is similar with the distributed components in the energy domain, like battery storages, PV systems, electric cars etc.

In addition to P2P systems, studies of multiagent systems (MAS), e.g. (Shoham and Leyton-Brown, 2009), have investigated concepts with specific relevance for BSNs. With MAS, autonomous (network) entities are called agents. In our BSN, single participating households or household devices are modelled as agents. These households, or even the battery storages in the households, regularly communicate their potential utilization at 15-minute intervals to their BGO. With this information in mind, the BGO then requests the whole BSN to provide/consume a specific part of this potential to/from the grid to keep the group balanced. At this point, the BSN participants jointly decide how to fulfil this request through distributed consensus finding. MAS provide a number of algorithmic options for the BSN participants, e.g. distributed constraint optimization, negotiation, auctions, voting or mechanism design.

A further, nascent technology – called blockchain – represents an apparent symbiosis of P2P and MAS technologies, and is currently gaining in importance in the energy domain (EventHorizon, 2017). A blockchain network represents a P2P network with a distributed consensus algorithm at its core. Additionally, through the abstraction of 'smart contracts', network participants are able to cooperate as is the case with MAS. Therefore, we are investigating the potential of blockchain as technology base for the envisaged decentralized BSN or if it is necessary to stick to more mature technologies.

A key constraint is the identification of a suitable solution for integrating the BSN-algorithms into – existing – household's energy or home automation system components. Hence, technologies that allow for the simple deployment of the developed BSN algorithms to these energy system devices are also part of the solution concept. In this aspect, container technologies like (Docker, 2017) and especially (Docker Swarm, 2017) for the realization of a reliable decentralized solution are complementing the concept.

***Social implications***

Especially if grid and/or system relevant applications require active coordination by third parties e. g. balance group managers or grid operators, one crucial aspect for the successful implementation and operation of such a BSN is the willingness and acceptance of storage operators (particularly private owners) to give access to external stakeholders. In order to assess this willingness of current and potential operators of home storage systems to participate in such a BSN, an online survey has been conducted. This assessment should serve as a proxy for the social implications of a BSN for system and/or grid-relevant applications.

The survey form contains up to 8 mainly closed-ended questions focussing on social aspects like motivation, risks, opportunities, framework conditions and incentives, as well as additional demographic and technical questions. With the support of the Vienna and Styria funding agencies [1] as well as of the national "Climate and Energy Fund", the survey was distributed to about 20,000 operators of home storage systems and/or a PV system.

Within 3 weeks, the survey had been completed by about 2,300 respondents, of whom 257 PV operators already owned a battery storage system. This meant that about 11 % of the PV owners originally contacted were included in the study sample. The data were analysed mainly using descriptive statistical analysis using Excel and SPSS.

The results of the survey show a high willingness of PV operators (with or without a battery storage system) to participate in a BSN for system and/or grid-relevant applications, although subject to certain conditions. While only 10 % of the sample would participate without further conditions, almost 75 % would agree to participate only under certain framework conditions. This result emphasizes that the development of these framework conditions is a crucial factor for the success of such a network.

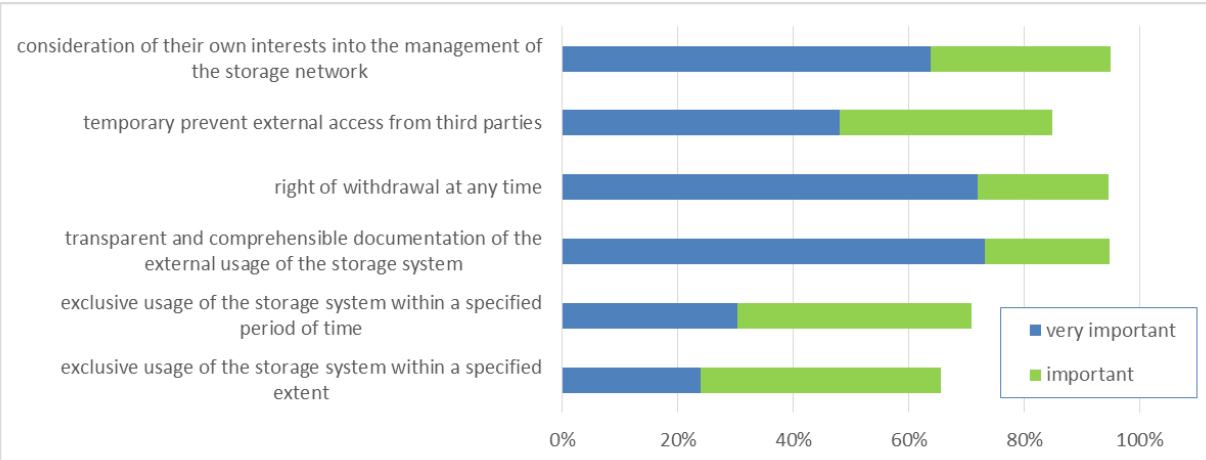

Figure 4. Importance of selected potential framework condition for the participation in a grid- and/or system-relevant BSN

Those 85 % of the sample who stated that they were basically willing to participate (even though only under certain framework conditions) were asked about the importance of selected framework conditions, their motivation and possible (financial) consequences regarding a potential participation. As displayed in Figure 4, the right to withdraw at any time, as well as a transparent and comprehensive documentation of the use of the storage system were ranked by a majority of respondents as 'very important' (72.01 % and 73.12 %) conditions, shortly followed by their own interests being considered in the management of the storage network (63.74 %). Asked about their motivation to participate, top-ranked answers were the contribution to 'increased security of supply' (42.65 %), and 'a higher share of renewable energy in the overall system' (40.62 %). In contrast, additional earnings

[1] Vienna: Municipal Department 20 - Energy Planning, Styria: Department 15 Energy, Housing, Technology

opportunities were considered to be ‘very important’ by only one quarter of the respondents (25.71 %).

The study also gives insights into the relevance and suitability of different incentives and financial compensation for the additional use of their own storage systems and the associated (financial) impacts on the owner. Regarding additional incentives for participation, 80 % of respondents seem to consider financial compensation for additional costs or foregone revenues to be sufficient for participating in such a BSN. This confirms that financial interests are not a decisive factor for participation. This is particularly interesting in contrast to the responses of battery storage owners’ statements about their initial motivators when buying the storage, in which ‘improvements in the profitability of their PV’ plant was stated by 97.5 % to be ‘very important’. Further analysis will therefore focus on the differences and similarities of respondents with and without their own battery storage.

**Conclusions**

Beside the usage of battery storage systems to limit the maximum grid feed-in of a PV system, several additional grid- and/or system-relevant applications for battery storages are available.

A case study of the impact of using a decentralized autonomous energy storage system, utilizing only local data for training a neuronal network as consumption forecast input, will provide more data to allow a better consumption prediction of wider application areas (residential, industry, different geographical areas, etc.). The objective of the system so far is to improve the coordination of system planning and to even out load peaks. A more advanced system could be designed to allow multiple objectives or to work on multiple buildings. A different objective could be to provide additional services such as trading between buildings in a micro-grid, or emergency functionalities to always allow building evacuation or energy redundancy for safety critical systems. A future integration in building management or smart home systems, an industry which has been progressing substantially in the last decade, can be considered very likely. The rapid advancements of both software and hardware solutions specialized in machine learning in recent years allow faster training of small neural networks. Although the development of self-learning systems able to predict energy demand is still a challenge, it is now computationally feasible to create a self-learning system on cheap off-the-shelf hardware. Cloud-based high-performance computing enables multiple models to be created in parallel, in which parameters of the models can be optimized with various methods (Grzesiak et al, 2007) (Goodfellow et al, 2014) in feasible time windows. This allows more generic systems to be designed, dynamically optimizing the parameters in parallel with the flow of new data. Available data for research is the biggest limitation for the use of deep learning techniques in energy consumption estimation (Mocanu et al, 2016).

Especially if grid- and/or system-relevant applications require active coordination and external access to the home storage system by third parties, one crucial aspect for the successful implementation and operation of a BSN is the willingness of storage operators to participate. In this context, the results of the survey show promising prospects for the successful implementation of a BSN for system- or grid-relevant applications. In total, almost 85 % of the sample would agree to participate, even though the majority only under certain framework conditions. Furthermore, the results emphasize the importance of transparent and comprehensible framework conditions and well-designed instruments for its implementation and management from the operators’ perspective. Participation is predominantly ideologically and technically motivated (contribution to the energy transition and to a high supply service), financial aspects only play a minor role. Further analysis will discuss the results of the survey in relation to relevant framing conditions, as well as potential bias within the sample due to characteristics of the participants as 'early adopters' in the study, or effects of social desirability in their response behaviour.

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